



Linking global climate change to local water availability: Limitations and prospects for a tropical mountain watershed

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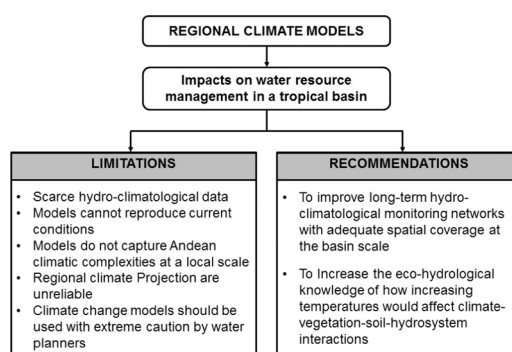
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HIGHLIGHTS

- Water managers rely on regional climatic models to plan future strategies.
- We found strong biases in climatic model predictions compared to observed data.
- Regional models are inappropriate to inform water planning to face climate change.
- We need to improve monitoring and ecohydrological knowledge in tropical regions.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:

Received 16 June 2018

Received in revised form 19 September 2018

Accepted 24 September 2018

Available online 24 September 2018

Editor: Henner Hollert

Keywords:

Climate change
Water availability
Water uses
Climatic model bias
Quito
Tropical mountains

ABSTRACT

Bridging the gap between the predictions of coarse-scale climate models and the fine-scale climatic reality is a key issue of hydrological research and water management. While many advances have been realized in developed countries, the situation is contrastingly different in most tropical regions where we still lack information on potential discrepancies between measured and modeled climatic conditions. Consequently, water managers in these regions often rely on non-academic expertise to help them plan their future strategies. This issue is particularly alarming in tropical mountainous areas where water demand is increasing rapidly and climate change is expected to have severe impacts. In this article, we addressed this issue by evaluating the limitations and prospects in using regional climate models for evaluating the impact of climate change on water availability in a watershed that provides Quito, the capital of Ecuador, with about 30% of its current water needs. In particular, we quantified the temporal and spatial discrepancies between predicted and observed precipitation and temperature, and explored underlying mechanisms at play. Our results provide a strong critique of the inappropriate use of regional models to inform water planning with regard to adaptation strategies to face climate change. As a multidisciplinary group composed of hydrologists, ecologists and water managers, we then propose a framework to guide future climate change impact studies in tropical mountain watersheds where hydro-climatological data are scarce.

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1. Introduction

Climate change is associated with a variety of physical and biological effects that impact water availability for human uses (Kundzewicz et al., 2008). In particular, climate change is expected to strongly modify both temporal and spatial patterns in temperature and rainfall, with important consequences on hydrological regimes and aquatic biota (Kilsby et al., 2007; López-Moreno et al., 2011; Woodward et al., 2010). According to outputs of climate model simulations, higher temperatures are likely to increase evapotranspiration, causing changes in large-scale precipitation patterns and the frequency of extreme events (Buytaert et al., 2010). These changes are also expected to strongly affect different key parameters of hydrosystems such as stream flow, soil moisture and groundwater storage, as well as water provision to people (Kløve et al., 2014; Mishra et al., 2018).

The standard procedure for studying the impact of climate change on water resources at a basin scale is to downscale climatic variables – both control (CTL) and future scenarios – obtained from the outputs of global or regional climatic models (GCMs, RCMs). Given the bias of most RCMs under CTL scenario, different downscaling techniques and bias-correction methods have been developed to estimate the difference in climate outputs (mean, variability) between current and future conditions (González-Zeas et al., 2012, 2014; Pulido-Velazquez et al., 2011; Teng et al., 2015). These corrected values then feed a hydrological model that determines the available water resources in a watershed of interest (Gosling et al., 2011). Over the last three decades, there have been many attempts to use climate model projections to inform water management decisions in the face of climate change mean trends and variability (e.g., Chávez-Jiménez et al., 2013; Mourato et al., 2015). Several studies have noted that climatic conditions recorded at weather stations in local watersheds may strongly differ from those predicted by global and regional climate models (e.g. Gudmundsson et al., 2012; Piani et al., 2010), therefore limiting the application of climate change models for sound predictions of water resource availability. While innovative methods to alleviate these challenges continue to be developed in many high-income countries (e.g. Maraun, 2016; Turco et al., 2017), the situation is contrastingly different in most tropical regions where we still lack information on potential discrepancies between measured and modeled climatic conditions, in particular in mountainous watersheds.

There are several practical and conceptual reasons for being concerned with climate change predictions for water resource availability in mountain watersheds located in the tropical and sub-tropical belts. First, unlike temperate mountain regions, tropical mountains host many large cities and the growth trends of urbanization and population require increasing volumes of water to be extracted and transported (Jacobsen and Dangles, 2017). In the tropical Andes, the four major cities receiving water from high altitude sources (Bogota, Quito, Lima, La Paz) have experienced exponential growth coefficients between 1.82 and 2.42 over recent decades (Buytaert and De Bièvre, 2012). Population growth will be the main driver of increased stress on water resources in the future as water demand in the four major cities of the tropical Andes may rise by up to 50% in 2050. Second, there is growing evidence that the rate of warming is amplified with elevation such that many, high mountain ranges (>3000 m above sea level, m.a.s.l.) experience more rapid changes in temperature than environments at lower elevations. This process, known as elevation-dependent warming, is explained by the fact that several mechanisms (e.g. elevation-dependent changes in cloud cover and soil moisture) lead to enhanced warming with elevation (Mountain Research Initiative EDW Working Group 2015). Third, tropical mountain watersheds have permanent growing seasons resulting in well-developed soil and vegetation covers (e.g. páramos and bofedales in the Andes, prairies in Himalayas) and highly active biological communities when compared to temperate mountains. This implies that biological processes, which profoundly depend on temperature and humidity, may play a key role in understanding

climate change–water flow interaction in these systems. Last, due to the limited research capacity in climate and hydrological modeling in developing countries, water managers often rely on non-academic expertise (e.g. banks of development, private agencies) to help them plan their future strategies. Instead of conducting critical assessments of model fidelity, these experts generally use available global climatic predictions to run poorly parameterized climatic-hydrological models (due to a lack of data), thereby leading to weakly grounded predictions (e.g. Vergara et al., 2007). For all these reasons, hydrosystems in tropical and mountainous areas urgently require more attention to achieve sound management of water resources in the face of climate change.

To address this issue, this paper evaluates the limitations and prospects of RCMs in water resources availability in the Chalpi basin, a small watershed located in the Ecuadorian Andes at >3500 m.a.s.l. This watershed is part of the Papallacta system that provides Quito, the capital of Ecuador, with about 30% of its current water needs. We used climate projections previously implemented for the Andes and obtained downscaled predictions with the regional climate model PRECIS. The main objective of our study was to assess the limitations of using RCM outputs (precipitation and temperature variables) to predict future water availability in the Papallacta system. Our methods were not focused on testing different downscaling methods at basin scale or bias-correction techniques for improving RCM estimates under CTL scenario, because it is unclear if the bias correlation applies in a future climate when the underlying dynamics of the climate system have change under global warming. Our specific objectives were: (i) to evaluate the limitations of using outputs of RCMs at a local scale, (ii) to quantify the temporal and spatial discrepancies between predicted and observed precipitation and temperature under current and future scenarios, (iii) to evaluate the variability in extreme rainfall events in the watershed and (iv) to propose a framework to guide future climate change impact studies that could be relevant for water managers in tropical mountainous regions.

2. Material and methods

2.1. Study site

The Chalpi basin is one of the main sources of water supply to the Papallacta System, which provides potable water to about 30% of the 2.6 million people city of Quito. Quito's water utility (EPMAPS) has built different hydraulic structures in the upper part of this basin (e.g., water intakes and reservoirs) to withdraw water from the river and to transport it through pipes to the city. This system, together with other existing systems (Pita, Mica, Atacazo and Noroccidente systems, see Fig. 1a), covers the entire demand of drinking water for the city. The study basin is located in the continental division of the Pacific and Amazon, specifically in the headwaters of the Amazon basin. It has an approximate area of 95 km² with elevations that vary between 2880 and 4200 m.a.s.l. (Fig. 1b). Additionally, EPMAPS' long-term capacity expansion plan currently includes the construction of four new water intakes in the lower part of the basin, with the potential to significantly increase water supply reliability for the system by 2040. The basin is covered by soils and vegetation typical of the páramo ecosystem (high elevations wetlands), which are characterized by their high capacity for water interception, filtering and retention (see Appendix A, Fig. A1).

2.2. Meteorological data

Seven rain gauges and five climatic stations provided 10-minute precipitation and temperature data, respectively, for different periods between 2003 and 2016 (see Appendix A, Table A1 for details). The selection of stations with meteorological data allowed a reasonably good spatial coverage of the entire study basin, at different altitudes (Fig. 1b), especially during the period between 2008 and 2016

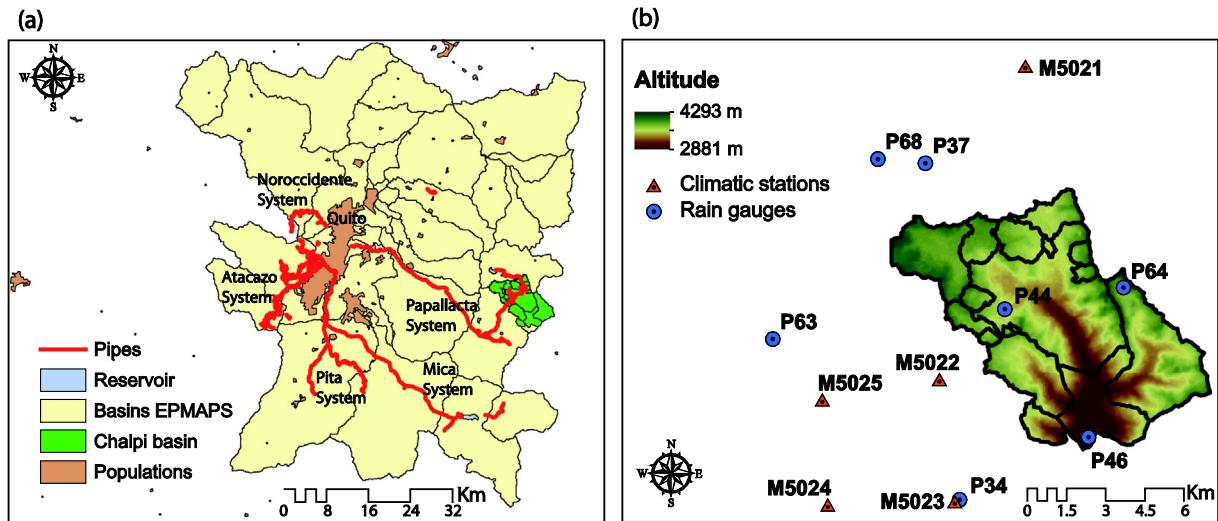


Fig. 1. (a) Location of study basin within the water supply system of Quito city. (b) Location of climatic stations and water intake structures in the Chalpi basin (see Appendix A, Table A1 for further details on the data associated with each station).

(Table A1). Although elevations in the basin vary between 2880 and 4200 m.a.s.l, the events of snow only occur in anomalous years, or they may not happen in some years, and they can be minimal and of short duration (hours), so they definitely not represent an undercatching problem. Besides, precipitation is very heterogeneous in mountainous regions, so this could lead to large uncertainty in the observations. Moreover, over the western slope of Ecuador, a single rainfall maximum occurs between 1000 and 3500 m.a.s.l. (Bendix and Lauer, 1992) as like observed in other mountainous ranges (Anders and Nesbitt, 2014; Collados-Lara et al., 2018).

We modeled the spatial patterns of precipitation and temperature in the study watershed using two interpolation methods, inverse distance weighting (Chen and Liu, 2012; Cressie, 1993) and co-kriging (Pebesma, 2004; Vicente-Serrano et al., 2003), respectively. These procedures allowed generating maps of mean monthly isohyets and isotherms for the study period (2008–2016). Furthermore, we used 1) the Worldclim dataset to obtain average monthly climate data of precipitation and temperature for 1971–2000 with a spatial resolution of 30 s (approximately 1 km², Fick and Hijmans, 2017) and 2) the Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset (Funk et al., 2015), which is based on high-resolution observations of infrared Cold Cloud Duration (CCD). CHIRPS uses the Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis version 7 (TMPA 3B42v7, Huffman et al., 2007) to calibrate CCD rainfall estimates and provides monthly precipitation from 1981 to present at a resolution of 0.05°.

2.3. Climate change simulations

Climate change scenarios were obtained from the International Center of Tropical Agriculture based in Colombia (CIAT, <http://www.ccafs-climate.org/>). The CIAT produces dynamically downscaled meteorological variables from the PRECIS RCM, an atmospheric and land surface model focused on the Andes (PRECIS, 2001). Monthly precipitation and temperature data were obtained in ARC GRID format (decimal degrees and datum WGS84) with a resolution of 25 min (cells of approximately 50-km sides). PRECIS provides simulations under a control scenario (CTL) and future emission scenarios. We used two of them, A1B (intermediate growth in emissions) and A2 (rapid growth in emissions), which reflect intermediate and high greenhouse gas emission scenarios, respectively. These two scenarios were run using the MPI_ECHAM5 and MPI_ECHAM4 GCMs, respectively, which produce the boundary conditions for PRECIS. The CTL scenario corresponds to the period between 1961 and 1990, while future scenarios were

calculated for the year 2040. RCM PRECIS outputs for South America Andes only provide mean values for a given period of data (and not data for individual years), thereby impeding us to calculate inter-annual variability.

2.4. Analyses

2.4.1. Observed data vs. simulations

We first quantified mean monthly precipitation and temperature values from the RCM under the CTL scenario (1961–1990) and compared them to observed data. Because our observed data correspond to a relatively short period (2008–2016), we used the information provided by Worldclim (1971–2000) and CHIRPS (1981–2010) datasets to count with at least 30 years of data. First, we assessed whether observed precipitation (2008–2016) presented a good adjustment with CHIRP predictions. Then, we evaluated to what extent the seasonal patterns of CHIRPS and Worldclim data were reproduced by RCM simulations (see Appendix C, Fig. C1 and C2") (2008–2016). Although the comparison used two different periods, it gave us a broad assessment of the reliability of RCM outputs for hydrological modeling. Then, for each of the two emissions scenarios, we evaluated the change in precipitation Δ_P and temperature Δ_T under climate change scenarios (CC) with respect to the control scenario (CTL) as follows:

$$\Delta_P = \frac{CC - CTL}{CTL} \quad (1)$$

$$\Delta_T = CC - CTL \quad (2)$$

Δ_P and Δ_T were calculated from the RCM grid cells over and nearby the watershed. Indeed, establishing predicted temperature and precipitation maps under different climate change scenarios would be paramount for water managers so that they can calculate water availability at a sub-basin level (see Fig. 1b). Following Janssen and Heuberger (1995) we used a bias indicator B between monthly observed (O) and monthly simulated (S) values of the variables, calculated as follows:

$$B = \frac{S - O}{O} \times 100 \quad (3)$$

2.4.2. Precipitation variability

As an additional analysis of potential climate change impacts in the watershed, we performed an analysis of extreme rainfall events over

14 years with a daily temporal resolution. Those events are of great interest to water managers, as they can threaten infrastructure during floods and provoke water shortages during severe droughts (Beguería et al., 2011; Vairavamorthy et al., 2008). Furthermore, several climate change simulations predict an increased frequency, intensity and unpredictability of extreme events in the future (Keath and Brown, 2009). In general, it is recommended to use at least 30 years of rainfall data to account for inter-annual variation in seasonal and annual means. Due to the lack of data in the Chalpi watershed, we assessed inter-annual variability by using the rain gauge (P34) with the longest data period (2003–2016). As the probability of extreme flood and drought events are directly related to precipitation, we calculated the 95th percentile of precipitation over the 14 years ($\%95 = 11.5$ mm) and the number of days with no rain as metrics of precipitation extremes (Barton and Giannakaki, 2016; Coles, 2001; Fukutome et al., 2015). Unfortunately, it was not possible to compare observed vs. predicted precipitation variability because the annual PRECIS model data were not available.

3. Results

3.1. Analysis of precipitation and temperature under the CTL scenario

Based on the grid outputs for every month simulated by the RCM over the Chalpi basin (Fig. 2a and b), our results reveal an important overestimation of precipitation and temperature simulated by CTL climate models when compared to observed data (Fig. 2c and d). The

bias in the magnitude of precipitation is approximately 200% and predicted mean temperature is around 16 °C instead of the measured 6 °C. Importantly, there were strong seasonal discrepancies in precipitation patterns between simulations by RCM and observed data, with a complete inversion in the timing of the rainy and dry seasons (Fig. 2c). The seasonal pattern of air temperatures, namely a slight decrease during the rainy season, was observed in both simulated and observed data (Fig. 2d).

To understand the mechanisms behind the difference in seasonality between observed data and the CTL scenario of the PRECIS, we evaluated precipitation bias at the scale of the whole country by drawing the differences between simulated (PRECIS) and observed (CHIRPS) rainfall data for all months. We found that PRECIS overestimated precipitation in the Andean cordillera (in particular the eastern slope), while the CHIRPS tended to under-estimate precipitation in the Amazon from July to September (Fig. 3). The RCM under the CTL scenario was better at capturing precipitation patterns on the Pacific coast where the rainy season occurs from January to April (see Appendix B, Fig. B1). CTL PRECIS estimations in the Chalpi basin followed climatic patterns observed in the Ecuadorian coast (wet from January to April, dry from May to September), hence the pattern observed in Fig. 2c. Also, the PRECIS model failed to represent the annual migration of the inter-tropical convergence zone, and produced rainfall hotspots between latitudes 1°N–2°S, which were not congruent with the reality. Importantly, it would be extremely difficult to apply bias corrections to these types of precipitation errors, which are indicative of a poor representation of the large-scale atmospheric circulation over the region.

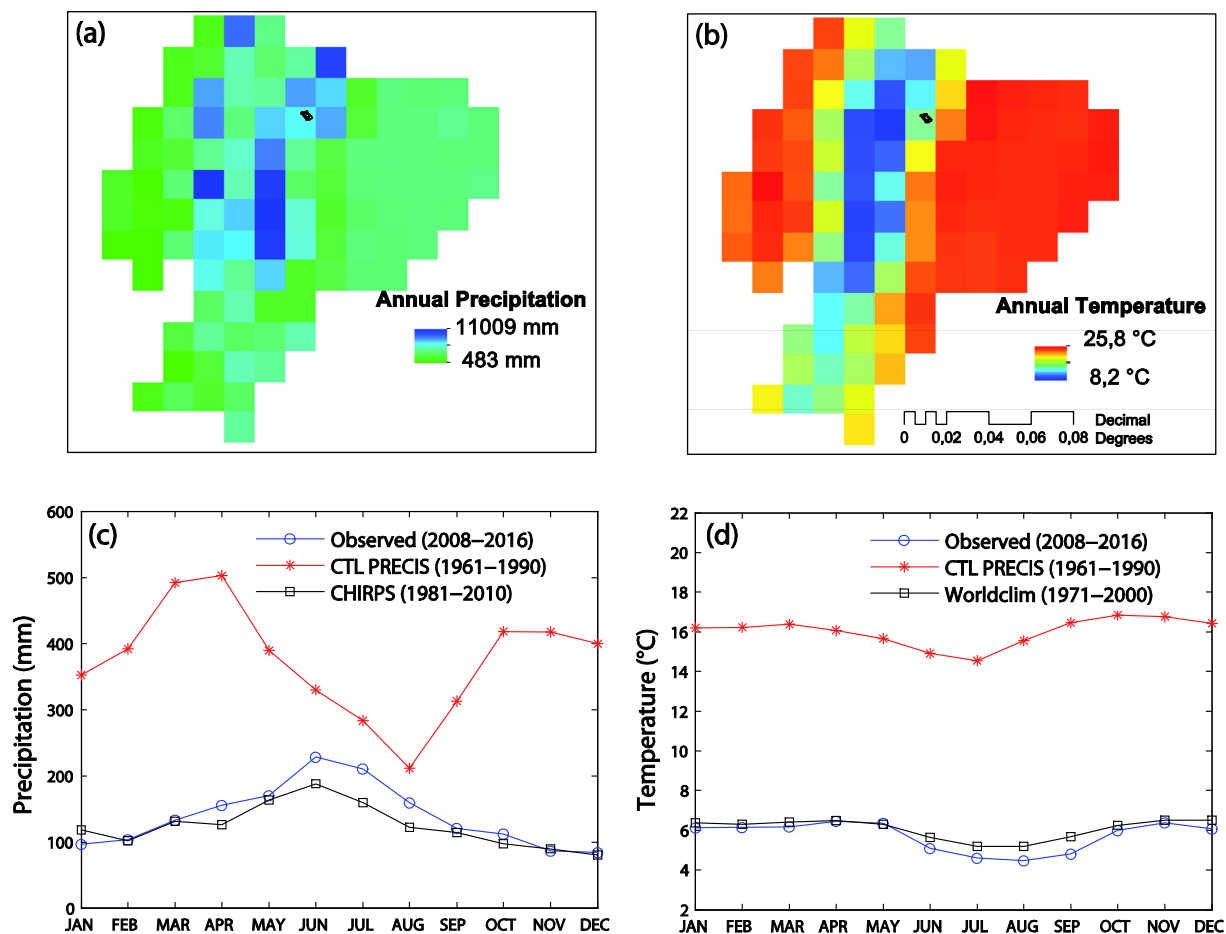


Fig. 2. Maps of Ecuador representing the spatial characterization of (a) annual precipitation and (b) annual temperature simulated by regional climate models under current scenario. Black symbols represent the location of the Chalpi basin, which provide Quito with potable water. The lower panels provide a temporal characterization of CTL scenario of the PRECIS (1961–1990), observed data (2008–2016) and CHIRPS (1981–2010) for (c) monthly precipitation and CTL scenario of the PRECIS (1961–1990), observed data (2008–2016) and Worldclim (1971–2000) for (d) monthly temperatures.

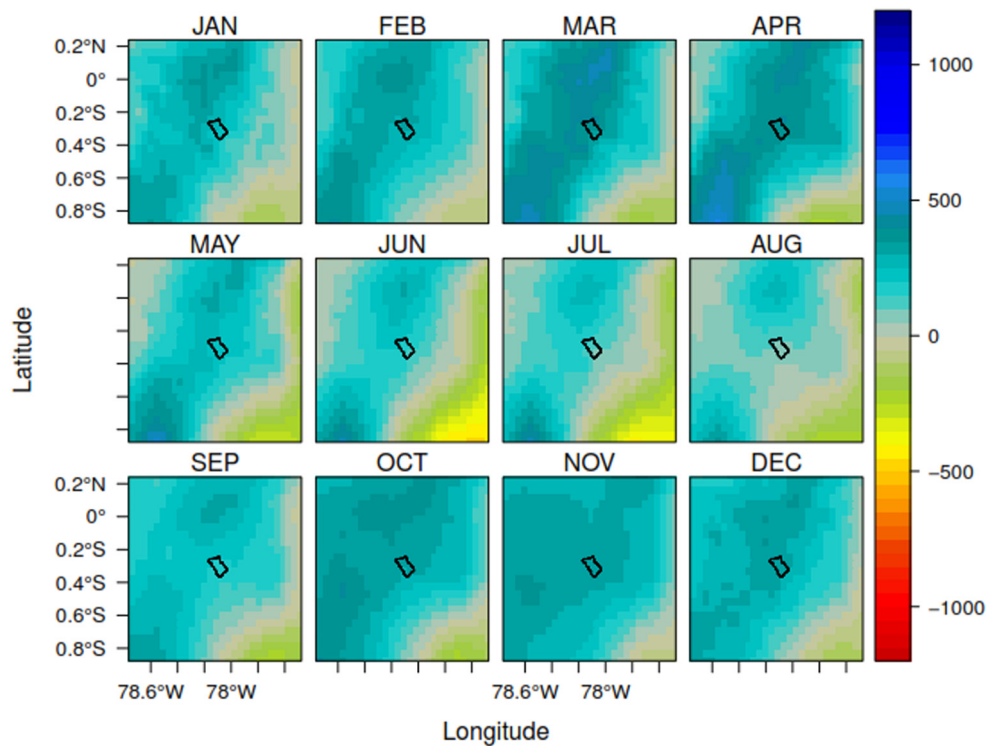


Fig. 3. Monthly spatial bias of precipitation (mm) calculated as the difference between RCM simulations under CTL scenario (PRECIS) and “observed” CHIRPS data. Black polygon indicate the study basin.

Any precipitation bias in the CTL scenario may change in a future period if the atmospheric circulation shifts under anthropogenic warming. This makes it virtually impossible to verify that projected changes in precipitation are accurate, and not just an artifact of a bias in atmospheric circulation that is changing from baseline to future conditions.

3.2. Analysis of precipitation and temperature under climate change projections

In view of the strong biases of PRECIS to model observed climatic data, future predictions would likely be unreliable. Yet, as an illustrative exercise, we mapped the relative change in average monthly precipitation (Δ_P) and temperatures (Δ_T) in the Chalpi basin and surrounding cells for two emission scenarios, A1B and A2 (Fig. 4). Overall, Δ_P maps showed highly inconsistent patterns both spatially and between both scenarios, in particular for precipitation. The A1B scenario predicted an overall decrease in precipitation by 2040 (ranging from 5% in August to 39% in September), except in May that presented an overall 2% increase in precipitation. Under the A2 emission scenario, predictions were even more erratic as precipitation decreased by 8%, 7%, 31% and 39% in January, June, November, and December, respectively, while the other months it increased from 3% (July) to 88% (August). For the two climate change scenarios, Δ_T maps showed an overall increase in temperatures in the Chalpi basin. These increases varied between 1.3 °C (April) and 2.0 °C (September) under the A1B scenario, and from 2.4 °C (September) to 3.4 °C (January) under the A2 scenario. For both precipitation and temperature, PRECIS predictions were highly erratic spatially (in particular for the A2 scenario), with differences between adjoining cells as high as 2.5 °C and 100% of precipitation. There are many months where the grid cell over the Chalpi basin was straddled by other grid cells with opposing signs of precipitation change. The implication is that small spatial biases in PRECIS could lead to large differences in projected precipitation change in this transition zone, reducing the reliability of projected changes for the Chalpi basin.

3.3. Precipitation variability

Beyond testing the relevance of climate change models for the Chalpi basin, we also analyzed precipitation variability across years (Fig. 5). Overall, daily precipitation variability was comparable among the 14 years of data, ranging between 0 and 40 mm·day⁻¹ (Fig. 5a). The number of days without rain was significantly more variable among years (Fig. 5b), than days with precipitation > 11.5 mm (percentile 95th). In particular 2005, presented an exceptionally high number of days (120) without precipitation. This pattern was confirmed when plotting the cumulative number of extreme events for the 14 studied years (Fig. 5c–d). All cumulative number of days with high values of rainfall curves had a similar S-shape through time, with an abrupt increase in the number of rainy days between the day 150 and 200 (Fig. 5d), which corresponds to the start of the rainy season (see Fig. 2c).

4. Discussion

4.1. Limits of climate predictions

Bridging the gap between the predictions of coarse-scale climate models and the fine-scale climatic reality of mountainous watersheds is a key issue of hydrological research. Indeed, our study confirmed the common view that regional climate models do not adequately capture the reality of the climate in such settings (Sharma et al., 2007; Teutschbein and Seibert, 2012; Varis et al., 2004). This result was not surprising as mountain ranges provide key boundary conditions for climate modeling (Fekete et al., 2002; Viviroli et al., 2011). RCM output biases have been well documented in the literature (Marcos et al., 2017), and it is generally recommended to eliminate such bias before using predicted climatic values as inputs for hydrological models (Christensen et al., 2008). However, in the case of precipitation, our study revealed that not only the mean predicted values were much higher than observed ones but also that the seasonal pattern in

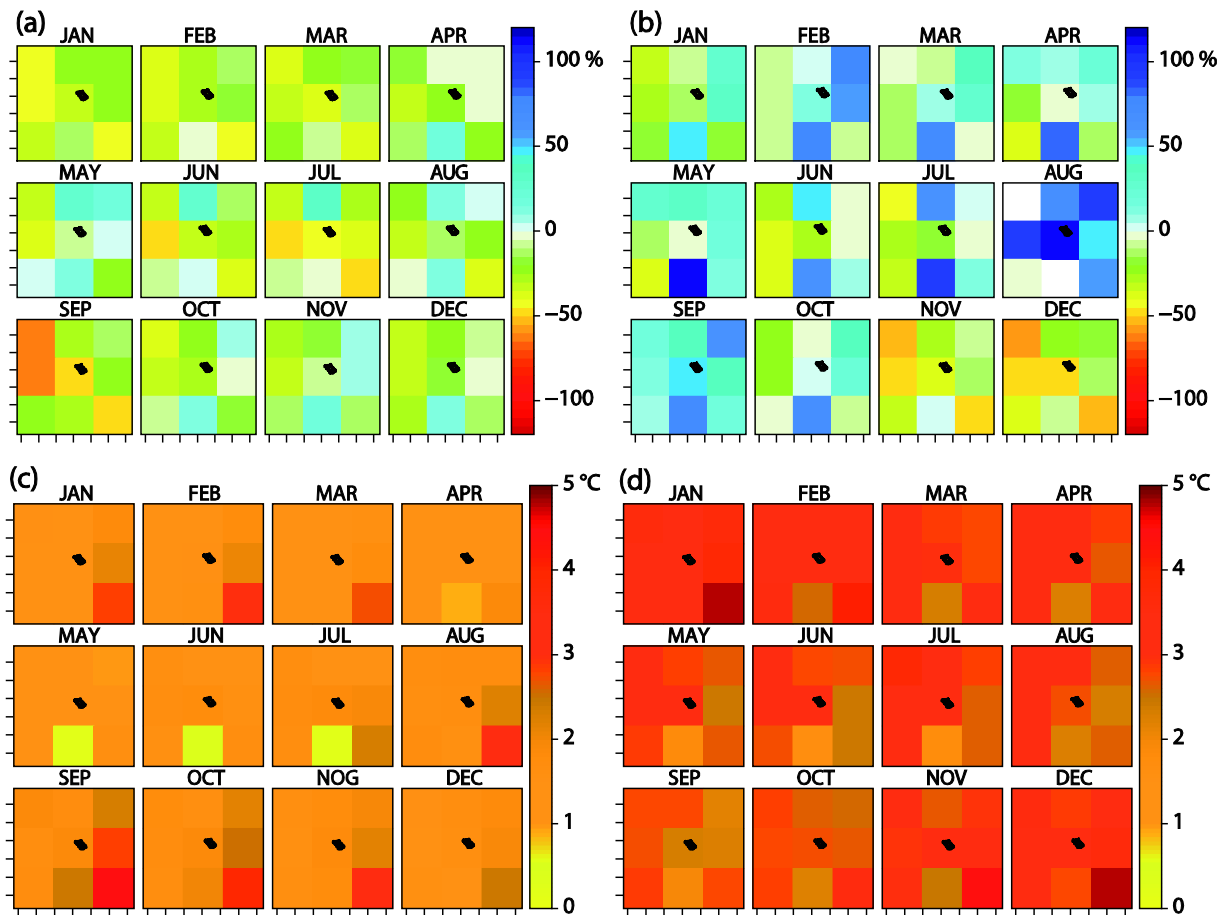


Fig. 4. Differences in predicted and current precipitations Δ_P (% a, b) and temperatures Δ_T ($^{\circ}\text{C}$, c, d) under A1B (a, c) and A2 (b, d) emission scenarios with respect to CTL scenario for the year 2040. Output grid resolution of the RCM is approximately 50-km wide. Black symbols represent the Chalpi basin.

precipitation was completely unrealistic (see Urrutia and Vuille, 2009 for similar conclusions in the tropical Andes). In our case, the predicted precipitation regime in the Chalpi basin, located on the Amazonian side of the Andes, clearly follows climatic patterns from the Ecuadorian Pacific coast (Erango et al., 2018). This suggests profound limitations in our understanding of regional climate simulations under a control scenario, which cannot be fixed by a simple bias correction of RCM outputs (Addor et al., 2016; Foley, 2010). Importantly, our study case clearly illustrates that we are not only facing a “climate prediction” issue but also an inability to reproduce the current climatic situation (Buytaert et al., 2010). Bias between observed and predicted climates can vary greatly and randomly among adjacent RCM grid cells, which reveals that these models do not produce robust results at a local scale for the region considered.

While several authors (e.g., Marengo et al., 2009; Alves and Marengo, 2010; Canziani and Carbajal Benitez, 2012) used the PRECIS RCM to simulate precipitation and temperature patterns over South America, there are still systematic errors in the regional model. These are related to the physics of the model (convective schemes, topography, and land-surface processes), the lateral boundary conditions, and possible biases inherited from the global model (Palmer and Weisheimer, 2011; Bruyère et al., 2014). According to Buytaert and De Bièvre (2012), the Andean region clearly presents higher variations in climate model simulations compare to surrounding areas (Pacific Ocean and Amazon basin). This strongly suggests that the difficulties in representing the current climate are a major source of uncertainty in tropical mountains and that future projections should be treated with care (Urrutia and Vuille, 2009). One of the limiting factors regarding the use of RCM information is the scale misalignment between the

output of the climate models and the scale use for water availability predictions (basin scale, Wood et al., 2002) so that several studies have developed downscaling techniques to overcome this deficiency (e.g., Pulido-Velazquez et al., 2011; Gutmann et al., 2014). Another factor that limits the use of RCM simulations is its bias with respect to observed data. Bias-correction techniques consider the influence of specific statistical metrics (e.g., mean and variance, Rätty et al., 2014; Pulido-Velazquez et al., 2017).

The difficulty of RCMs to simulate climatic patterns at a local scale makes their applications for hydrological simulations very hazardous, particularly in the context of climate change predictions (Wood et al., 2004). A few studies recommend using an ensemble of models for covering these uncertainties (e.g., Graham et al., 2007; Velázquez et al., 2013), yet when working at a local scale, such approaches generally do not substantively improve the reliability of predictions (Kjellström et al., 2010; Solman et al., 2013). Besides, the spatial scale of average precipitation should be large enough to preserve topographical gradients and reduce random errors (Wong and Chiu, 2008). Consequently, the use of larger spatial scales from RCMs produces a wide range of future patterns but cannot account for the fine-scale complexities that influence localized hydrological processes (Miles and Band, 2015). Additionally, several uncertainties are linked to RCMs such as the choice of the GCM (wide variability between models, especially in precipitation), the parameterization of the spatial scale reduction, and the bias when comparing with observed data (Déqué et al., 2007). These factors limit the ability of climate models to quantify the behavior of climatic variables at basin scales and the possibility to evaluate the interaction between climate, water, land use and their influence on ecosystem processes (Martin et al., 2017).

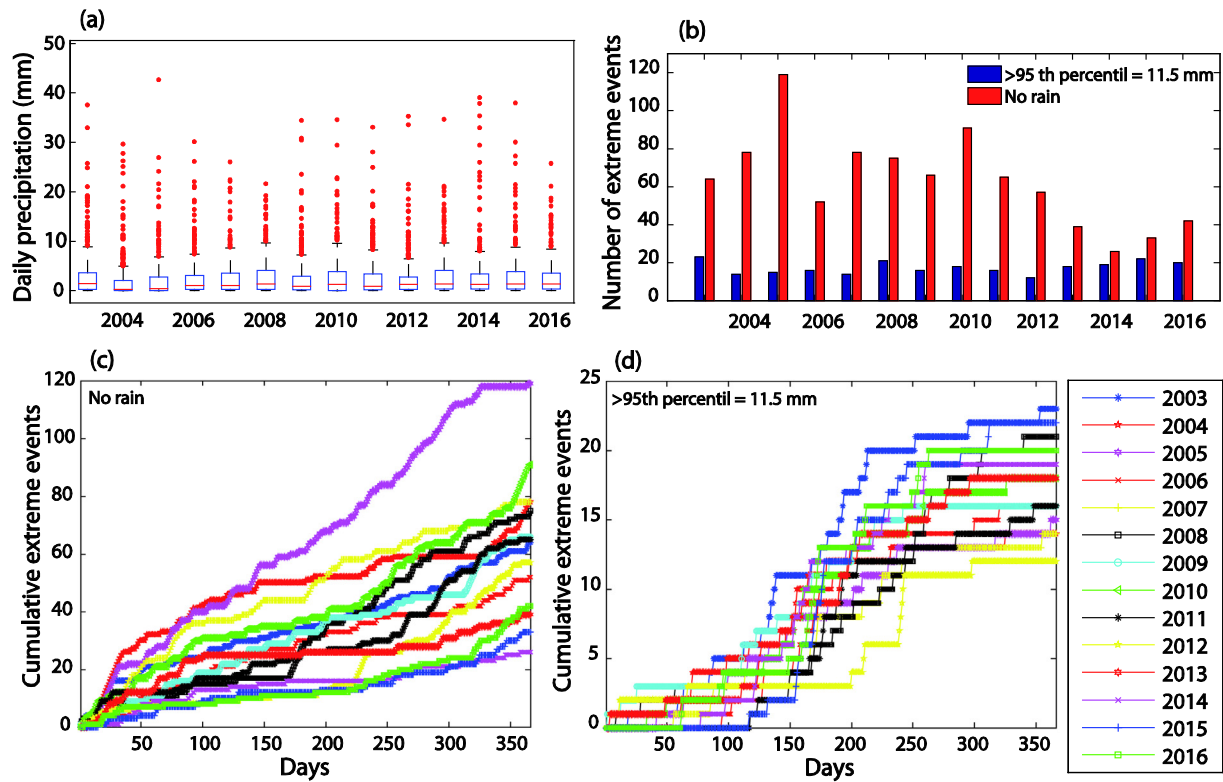


Fig. 5. Extreme precipitation events registered by the P34 rain gauge (see Fig. 1b) during the period 2003–2016: (a) annual variability of daily precipitation. (b) Number of extreme events for the higher values of precipitation (95th percentile) and number of days with no rain, (c) cumulative number days with no rain and (d) cumulative number of days with heavy rainfall (95th percentile).

4.2. Critical issues to improve water availability in changing tropical Andes

Our point here is not to critique climate models, as they represent unique and invaluable tools to better understand climate dynamics at large scales. However, we strongly critique the inappropriate use of these models to inform water planning with regards to adaptation strategies to face climate change. We argue that instead of developing and funding studies on water availability based on GCM and RCM predictions, water planners in tropical mountain regions should rather focus on two main objectives: (i) to improve climate and hydrological monitoring networks and (ii) to increase the ecohydrological knowledge on how increasing temperatures would affect climate-vegetation-soil-hydrosystem interactions.

4.2.1. To improve climate and hydrological monitoring networks

Mountain massifs can have a marked effect on climate by affecting the movement of frontal systems, as well as through a local topographic influence on airflow and resulting orographic precipitation and winds (Jacobsen and Dangles, 2017). For these reasons the deployment of automatic weather stations in mountain watersheds is crucial to have a better grasp on the relative importance of altitude and local effects on climate to improve our climate prediction models (Muñoz et al., 2010). Long-term meteorological stations (with >20 years of records) are, however, extremely sparse at high elevations. For example, out of 7297 stations in the Global Historical Climatology Network, only 191 (3%) are above 2000 m.a.s.l. and 54 (0.7%) above 3000 m.a.s.l. (Mountain Research Initiative EDW Working Group 2015). Moreover, most of the meteorological stations in mountain regions are located in valleys, meaning that slopes and peaks are under-represented in resulting data. This can have profound consequence for water flow predictions, as illustrated by significant incongruences between measured discharges and rainfall data in the Chalpi basin (DG, unpublished results). There is therefore an urgent

need for a greater coverage of climatic stations, especially in the higher altitudes of the basin. This is an important issue, taking into account that several key infrastructures that withdraw the water from the basin for urban supply are located at high altitude (see Fig. 1b).

Moreover, long-term time series of climate would be invaluable for the development of innovative methodologies for testing the resilience of water systems to climate variability, for instance by supporting the construction of stochastic weather generators to drive water system sensitivity analyses. Stochastic weather generators are computer algorithms that produce series of synthetic daily weather data, and are fit on existing meteorological records to ensure the characteristics of historic weather emerge in the daily stochastic process (Wilks and Wilby, 1999). If enough data are available to fit these models, they can be used to generate plausible sequences of weather that have not been previously observed. These sequences can then be used to force hydrologic and water system models at the local scale, and to test the robustness of water system performance under a wider range of plausible climate than currently exists in the observed record (Hutchinson, 1995). Further, weather generator parameters can be perturbed to systematically alter the underlying climate that is produced, enabling an alternative method to conduct climate change impact assessments for local water systems that does not depend on the output GCMs or RCMs, which may have underlying biases that make them difficult to directly use in local water planning exercises (Confalonieri, 2012; Jones, 2000; Steinschneider and Brown, 2013; Steinschneider et al., 2015). This approach is likely to provide more actionable information to water managers regarding the sensitivity of their system to climate, and can be supported with just a few years of additional climate data in high tropical regions.

4.2.2. To increase the knowledge on how higher temperatures would affect climate-vegetation-soil-hydrosystem interactions

While there are strong uncertainties on future precipitation variability, predictions of temperature increases are much more consistent, as

reported by many authors (e.g. González-Zeas, 2010; Maurer, 2007) and the present study. Ecosystems at the coldest margins of life, in particular in the alpine belts, are particularly sensitive to warming effects because chemical and biological processes are generally more temperature sensitive in colder environments (Bell, 2012). As a result, any warming-induced changes in the functioning of the well-developed vegetation, soils and associated biological communities in tropical mountains may strongly affect hydrological regimes (Brown et al., 2005; Flores-López et al., 2016; Waddington et al., 2015). We propose that four main biologically-controlled processes in mountain watersheds should be further investigated to better predict the impact of climate change on water availability for human consumption (see numbers in Fig. 6). (1) At the climate-vegetation interface, altitudinal distribution shifts in vegetation and tree lines are well documented in many mountain regions worldwide (see Öztürk et al., 2015), with potential consequences on water (rainfall and fog) interception. For example, in the tropical Andes (Tovar et al., 2013), the natural vegetation below the páramo belt is mostly tropical montane forest whose hydrological production is considered to be high because of cloud interception (Buytaert et al., 2006). (2) Such vegetation changes may also affect water retention in soils as different plant species may have particular strategies in water needs and capture (Farley et al., 2004; López et al., 2017). (3) Eco-hydrological processes in the soil compartment are also likely to be greatly affected by changes in temperatures. Soil organic carbon accumulation in tropical mountains is due to the continuous vegetation cover, low air temperature and atmospheric pressure, and frequent waterlogging of the soils. Increased temperature (together with decreased moisture) may affect soil microbial communities thereby reducing carbon accumulation and soil depth (Delarue, 2016), with unknown, yet potentially strong, effects on water filtering and retention. (4) Finally, warmer climate may not only affect water quantity but also water quality. Increased heating in surface waters can boost the primary production in high altitude lakes, wetlands and reservoirs, triggering periodical natural eutrophication processes. Algal blooms, including those of toxic cyanobacteria, are likely to be more frequent in

a warmer climate, putting at risk the potability of water (e.g. Echenique et al., 2014; Roegner et al., 2013).

5. Conclusions

Our findings were generally consistent with the expectation that regional outputs of RCM simulations are inadequate for predicting local scale climate conditions, especially in a mountainous basin with a great variability of topographical gradients. Under the CTL scenario, important biases were detected for both temperature and precipitation. The use of these models for water management should therefore be considered with extreme caution by water planners in the tropical Andes. In view of these limitations, we strongly advocate the need for water managers to (1) implement long-term hydro-climatic monitoring networks with appropriate spatial cover at watershed scales and (2) develop research on how warming temperatures may affect key hydro-ecological processes in the river system.

Acknowledgements

This work was part of the project “Développer des solutions pour la gestion durable et adaptative des ressources en eau dans les páramos de la ville de Quito (Équateur)” - CHALPI-FLOW - funded by the Agence Française pour le Développement (AFD), in collaboration with the French Research Institute for Development (IRD, convention no. 2017000345). The authors are thankful to the Quito's Water Company EPMAPS and the Water Fund of Quito FONAG, for providing the data.

Appendix A, B and C. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2018.09.309>.

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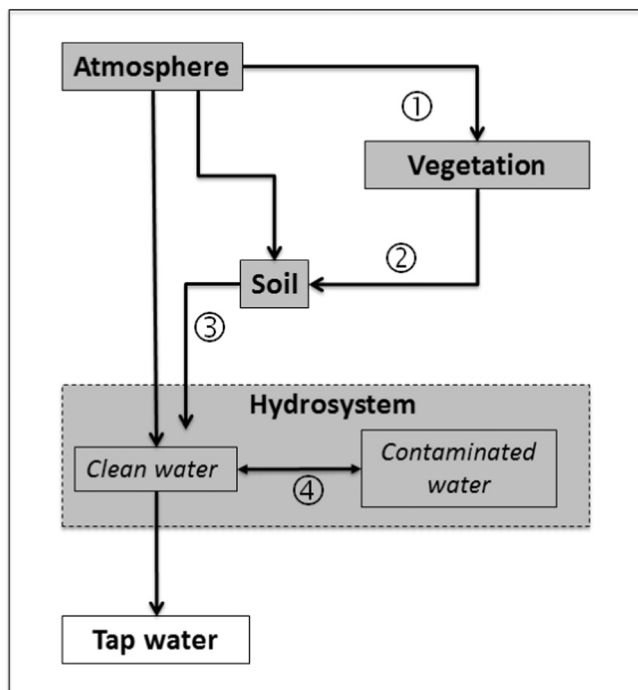


Fig. 6. A simple climate-vegetation-soil-water framework highlighting four key processes through which predicted increase in temperature may affect water availability for users in mountainous watershed of the tropical Andes. 1. Water capture, 2. Water retention, 3. Microbial processes and 4. Toxic algal blooms (see text for further details).

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